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Workers' Attitude Towards Bus Rapid Transit: Considering Dhaka, Bangladesh

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ABSTRACT

The Government of Bangladesh is planning to develop and implement Bus Rapid Transit (BRT) in Dhaka city. This paper presents a stated choice survey conducted to understand workers' attitudes toward BRT in Dhaka. The survey data are analysed using a multinomial logit (MNL) model to scrutinize social and economic factors' impact on participant's mode choices. Analysis results reveal that males, workers of higher age, education qualification, and income have a greater tendency towards choosing BRT.

Keyword: Bus Rapid Transit, Dhaka, Multinomial Logit Model, Stated Preference

INTRODUCTION

Dhaka is the capital city of Bangladesh. Like other megacities Dhaka is experiencing serious traffic congestion *(1)*. To reduce traffic congestion Government of Bangladesh is planning to implement Bus Rapid Transit (BRT).

Research questions addressed in this paper are: 1) Will the majority of commuters choose BRT for their work trip once implemented, and 2) how do travel attributes, and socio-demographics act differently on workers' mode choice decisions in the context of Dhaka compared to developed cities?

As very limited research exists on understanding commuter travel behavior and ultimately factors influencing BRT success in the context of a megacity in a developing country, this paper will have significant importance to practitioners and researchers.

This study uses a discrete choice modelling approach. A stated choice survey (SC) (hypothetical choice survey) was conducted in Dhaka from September 2011 to December 2012. As BRT has not yet been implemented in Dhaka, SC was used with a hypothetical BRT scenario amongst several choices for the work trip to understand factors important to workers' mode choice decisions. A mode choice model was developed using the SC data and "LIMDEP" software *(2)*. This paper starts with literature review, describes design of the SC survey, describes modelling analysis, and draws conclusions.

LITERATURE REVIEW

Travel Behavior Elasticity

Elasticity is defined as the measure of a change in response to a change in attribute. Many published and unpublished elasticity values of travel time and travel cost of different modes are available from research of other cities *(3)*. Elasticity values obtained from this research will be compared with elasticity value from European, US and Australian cities to understand the uniqueness of travel behaviour of a city like Dhaka. However, elasticity values for personalized public transport (PPT) (rickshaw, and auto-rickshaw known as CNG in Dhaka) are not available for developed cities, because such mobility options are unique to a developing city like Dhaka. BITRE *(3)* provides a comprehensive dataset on transport elasticity. Elasticities obtained by other researchers are usually provided in three ways; short run (less than two years), medium run (within five years), and long run (more than five years). Analyses based on short and medium run elasticity tend to understate results. According to Goodwin *(4)* and Litman *(5)* the long term impact would be twice the short term impact. Therefore, comparative analysis between very short run elasticity from this research and other cities will still indicate uniqueness of travel behaviour in a developing city.

Balcombe, Mackett *(6)* reported the impact of different factors on public transport in context of UK. They found that elasticity of in-vehicle time for bus ranges from -0.4 to -0.6.

Dargay *(7)* compared transit elasticity between England and France between 1975 and 1990, finding that income rise did not negatively impact French people's decision to use public transport, whereas it did impact English people's. Dargay and Hanly *(8)* studied demand for local bus service in England. They used a dynamic econometric model (separate short- and long-run effects) of per capita bus patronage, per capita income, bus fares and service levels. Their research found that commuters are relatively fare sensitive with wide variation of elasticity.

Deb and Filippini *(9)* determined elasticity values for 22 Indian states between 1990 and 2001. Their research found that for all states public transport demand is inelastic with respect to fare.

Goodwin *(4)* produced average elasticities based on UK and Europe studies. His research found that price impact increases over time. Therefore, short run impact will be always less than long run.

Hague Consulting Group *(10)* discussed impacts of car travel cost and car travel time, mainly for European cities, for the Trace project. Their research found that a 10% change in car time has a bigger impact on trips and kilometres than a 10% change in car cost. Findings also suggest that the short term elasticities of car km are about 50% of long run elasticities.

Hensher and Louviere *(11)* drew on a 1994 data set collected in 6 Australian capital cities to estimate a series of commuter mode choice models in the presence and absence of two 'new' alternatives (light rail and busway systems), to derive matrices of direct and cross point elasticities for travel cost and travel time. They found that constraining the variance of the unobserved effects to varying degrees tends to over-estimate elasticities sufficiently to distort the real behavioural sensitivity of specific attributes influencing choice.

Tsai and Mulley *(12)* identified public transport demand elasticity for Sydney, Australia. Their findings suggest that public transport demand price elasticity in Sydney is −0.22 in the short run and −0.29 in the long run. Wallis and Schmidt *(13)* updated and re-examined transport demand elasticity from Australia and New Zealand.

The literature review has identified many sources that produce original elasticity for different modes and many sources that compile elasticity from others' research. Table 1 lists the elasticity of travel time and in-vehicle travel time while Table 2 lists the elasticity of travel cost for different cities. However, no study was found which provides comparison of impact of travel factors between developed and developing countries' cities. This research provides a significant contribution to knowledge by providing this comparison in the context of Dhaka.

Model Choice Modelling for Dhaka and Other Developing Countries' Cities

Some studies have developed mode choice models in the context of Dhaka *(20, 21, 22, 23, 24, 25, 26, 27)*. However, only Enam *(25)* developed a mode choice model to perceive the preferences for mass rapid transit. Anam and Hoque *(28)* analyzed current performance of existing bus services and justified and proposed BRT road cross-section in an existing right of way (ROW). They compared the minimum requirement of BRT with corridor characteristics, existing roadway widths, condition, vehicular composition, land use pattern and obstacles along the corridor.

Nkurunziza and Zuidgeest *(29)* developed a binary choice model to understand commuters' preference for the proposed BRT in Dar-es-salam, Tanzania. Palma and Rochat *(30)* developed a NL model for the work trip of Geneva. They focused on the joint nature of the household car ownership decision and the decision to use the car for the work trip. Tushara and Rajalaksmi *(31)* developed a mode choice model for Calicut, India by applying MNL modeling. None of the research found in the context of Dhaka, and very limited research in the context of developing countries' cities, shed light on BRT uptake considering users' perception. A mode choice model result will give indicative answer of users' expectations of a BRT system for a city such as Dhaka.

STATED CHOICE (SC) EXPERIMENT

In normal SC survey design, each respondent is presented with a series of randomly drawn experiments having two options, for each of which they are asked to choose only one *(32, 33)*. For this research a non-traditional approach was adopted where each respondent was presented with one experiment having all of 16 possible options. Hess & Ross, Sanko and

Bilemere *(32-34)* argued for this non-traditional approach of SC survey design. This SC survey design is more realistic, less cumbersome and less time consuming. Providing several hypothetical experiments would have taken considerably more time and possibly caused confusion particularly for less educated respondents. This SC survey design is also new in that the surveyor explained the experiment in person to each respondent using illustrative cards. Therefore, explaining greater number of experiments would have been more time consuming. However, this SC survey design may cause some disadvantages. As the choices were given altogether, most respondents chose BRT as their preferred option. Therefore significant attributes for other modes are difficult to comprehend in one decision round.

Table 3 lists modes, attributes and their levels considered in the SC survey which was conducted on 426 samples. A paper based survey was chosen for its simplicity and convenience for face to face interaction. Because internet usage is infrequent in Dhaka, web based surveying was not feasible. Telephone survey was also not considered feasible due to high time and cost requirements. Glasow *(35)* stated that survey questions should be consistent with the education level of the respondent. As such the survey was written in simple Bangla, which for most respondents is easy to understand, as well as English.

In the initial run a number of modal options which incorporated BRT were included, with varying comfort vs cost points. Table 4 lists these different BRT comfort points. However this model proved difficult, so in the final model all BRT options were merged into one to understand workers' preference for BRT as a whole.

MULTINOMIAL LOGIT MODEL (MNL) ANALYSIS FOR DHAKA

Multinomial logit choice modeling is based on utility maximization theory *(37, 38)*. By MNL modeling the probability of choosing an alternative i from a set of j alternatives is expressed by Equation 1:

$$Pr(i) = \frac{\exp(v_i)}{\sum_{j=1}^{J} exp\left(v_j\right)} \tag{1}$$

Where,

$Pr(i)$ is probability of choosing alternative i

v_i is utility function of any mode

j is total number of alternatives

The choice set for model calibrated with SC data is: Bus (walk-bus-walk and walk-bus-rickshaw with average comfort level merged together to represent the current bus scenario); BRT (walk-bus-walk and walk-bus-rickshaw with good, better and best comfort levels merged together to represent the BRT system); Car & Personalized Passenger Transport (CPPT) (Rickshaw, CNG and Car merged together to represent CPPT); and Walk (Walk represent to those who chose walk in the SC survey)

A nested logit (NL) model is appropriate when the choices are interdependent and somewhat correlated *(38)*. However, for the SC model developed the choices are not interdependent. Therefore a NL model was inappropriate. A mixed logit (ML) model is appropriate for panel data. However, for a model calibrated with SC data ML model was inappropriate as survey respondents were asked to choose only one choice for the work trip from multiple options.

To select final attributes, a previous RP model was considered as described in the paper "Workers travel behaviour in the developing countries megacity considering Dhaka as a case study". This RP model showed that for Dhaka, gender, age, income, education, travel cost, and travel time in motion are significant attributes towards mode choice.

Table 5 lists attributes used in the model with the SC data while Table 6 lists model estimation result for model calibrated with SC data. Table 6 shows that coefficients of generic travel cost and travel time in motion have expected negative signs. Both attributes were considered significant as their *t* statistics were greater than 1.96 at a 95% confidence level *(39)*.

Postgraduate and gender are found as significant for the Bus mode. Therefore, those who are poor and female tend to use bus more than their male counterparts.

The *t* statistics of the income and age attributes are significant for BRT. As the coefficient of the income 0-5000 attribute is negative, those who are poor usually will not choose BRT. As the coefficient of the age attribute for BRT is positive, mature age workers are likely to use this mode for their work trip.

As the coefficient for postgraduate attribute is positive for CPPT, those who have postgraduate education tend to choose this car or PPT. As the age coefficient for CPPT is also positive, mature age workers are more likely to choose car or PPT for the work trip, which is attributed to their capacity to afford to do so.

As the coefficient of gender for Walk is negative, female workers tend to choose Walk. As the income 0-5000 coefficient for Walk mode is also positive, those who are poor tend to choose 'walk' more than other modes. As the age coefficient for Walk is positive, those older than 35 would choose Walk for their work trip.

MODEL VALIDATION

Overall Significance of Model

To determine the overall significance of the model with SC data, a log likelihood ratio test (-2LL test) was conducted and Pseudo R^2 value calculated.

If the log likelihood ratio value is less than critical chi square (χ^2) value at the 95% confidence level then the null hypothesis cannot be rejected (model is no better than the base model) *[40]*. If the log likelihood ratio value is more than the critical χ^2 value at 95% confidence level then null hypothesis can be rejected (model is better than the base mode) *(40)*. The -2LL value was determined to equal 396 while the critical χ^2 value was determined to equal 19.68 with 11 degrees of freedom at the 5 percent level of significance ($\alpha = 0.05$).

The pseudo R^2 value of the model was found to be 0.43, according to *(38)*, which is equivalent to about 0.80 of linear R^2. These results demonstrate that this model is significant.

Predictive Ability of Estimated Model

A comparison of the actual and the predicted mode share can provide an understanding of the performance of the estimated model. By comparing actual with predicted mode shares, the relative predictive abilities of the models can be determined *(41, 42)*. For this research the comparison between the actual and predicted mode shares was made in two ways:

a) Applying utility functions over all individuals with their actual attributes, and
b) Applying utility functions on a homogeneous groups of workers with sample average mode specific attributes

a) Applying utility function over all individuals with their actual attribute

Comparison shows that the model:

- underpredicts bus mode share to 2% less than actual mode share (in error by -7%),
- underpredicts BRT mode share to 9% less than actual mode share (in error by -15%),
- overpredicts car & PPT to 3% greater than actual mode share (in error by +50%), and
- overpredicts Walk to 8% greater than actual mode share (in error by +50%).

These results show no significant differences between actual and predicted mode share of bus and car & PPT. However the differences between observed and predicted mode share of both BRT and Walk are more than 5%.

b) Applying utility function on a homogeneous group of workers with sample average mode specific attributes

Actual and predicted mode shares from the estimated model were compared by applying utility functions on the homogeneous group ‘female workers without postgraduate education aged less than or equal to 35 and have income less than or equal to 5000 BDT’. These are respondents with sample average mode-specific attributes. The probability of mode share for each mode was calculated only once for this group. Comparison shows that the model:

- underpredicts bus mode share to 2% less than actual mode share (in error by -4%);
- overpredicts walk mode share to 2% greater than actual mode share (in error by +4%);
- predicts BRT mode share accurate to actual mode share; and
- predicts Car & PPT mode share accurate to actual mode share.

Model’s level of accuracy

The model’s level of accuracy can be measured from the sign of the coefficients, log likelihood ratio test and its predictive ability. According to Almasri *(40)* and Koppelman *(43)* if the model result does not provide the expected sign of coefficients then it is considered to be invalid. Coefficients for travel cost and travel time have the expected negative sign. The sign of the coefficients for other variables are also considered appropriate based on judgment.

The predictive ability of the model can be portrayed from the comparison between predicted choice and actual choice. Train *(41)* and McFadden and Talvitie *(44)* compared the different model’s predictive ability with the actual mode share. They considered the Root Mean Square Error (RMSE) of different models to understand the predictive ability of the models. RMSE offers a unitless measure of forecasting accuracy *(45)* and can take any positive value.

The unbiased model with the smallest RMSE value is the best predictive model. Comparing RMSE with other studies would give indicative figures of how the model’s prediction accuracy. Equation 2 was used to calculate model RMSE *(40)*.

$$RMSE = \sqrt{\sum(Q_i - R_i)^2} \tag{2}$$

Where,

$RMSE$ is root mean square

Q_i is actual mode share of alternative *i*

R_i is predictive mode share of alternative *i*

McFadden and Talvitie *(44)* found in their research that their best predictive model has RMSE 9.534. When the utility function was applied to all individuals in this study, RMSE was found to equal 13.00. When the utility function was applied to ‘poor female without postgraduate education aged less than or equal to 35’ group of worker (n=62) RMSE was found to equal 2.78. The result demonstrates that the model’s level of accuracy is acceptable for prediction.

ELASTICITY ANALYSIS FOR DHAKA

Travel time in motion in this research is defined as actual time commuters are moving plus travel time to/from the bus stop. None of the published elasticity values for public transport has been found to correspond directly to travel time in motion as defined in this research. Other studies use the variable of in-vehicle time, which does not include the access time to/from the stop. However, in-vehicle time elasticities from other studies offer an indicative comparison with the elasticity of travel time in motion.

Elasticity values of travel time in motion for all modes are as follows. Bold values represent direct elasticity of the respective mode while trailing values represent cross elasticity of the mode specified within parenthesis.

Bus: **-0.63**, 0.19 (BRT), 0.06 (car & PPT), 0.50 (walk)
BRT: **-0.37**, 0.47 (bus), 0.75 (car & PPT), 0.06 (walk)
Car &PPT: **-0.45**, 0.01 (bus), 0.05 (BRT), 0.01 (walk)
Walk: **-1.38**, 0.63(bus), 0.03 (BRT), 0.04(walk)

An elasticity value of travel time in motion less than 1 reflects that the mode is relatively inelastic to travel time in motion. Work trip tends to be less elastic than other trip purposes *(46)*. Table 1 lists elasticity values for in-vehicle travel time for other cities for comparison. Direct and cross elasticity values for bus travel time in motion in the model calibrated with SC data are similar to elasticity values for bus in-vehicle travel time for developed cities.

Table 1 reveals that people in developed countries’ cities are elastic to BRT travel time. It can be assumed that those commuters would be more elastic with travel time in motion as defined in this research, because it will be more than in vehicle travel time. SC model results for Dhaka show that commuters are slightly elastic with respect to BRT travel time in motion. This could be due to commuters in developed countries being wealthier and having more travel options, so can switch to other modes more easily when BRT travel time is increased.

As direct elasticity and cross elasticity values are less than 1, the modes are relatively inelastic to travel time in motion for CPPT. Increasing CPPT travel time in motion will increase the percentage of BRT more compared to each of Bus and Walk.

Table 1 reveals that, even though elasticities of car in-vehicle travel time for other cities do not include PPT, they can still enable an indicative comparison with elasticity of CPPT travel time in motion of the Dhaka SC model. The elasticity values of CPPT travel time in motion are very similar to elasticity values of car travel time in motion for developed countries’ cities.

Walk is relatively elastic with walk travel time in motion as the elasticity value is greater than 1. Commuters are slightly elastic with respect to walk travel time for Bus. However, workers are very inelastic with respect to walk travel time for each of BRT and CPPT.

SC model results show that workers are relatively elastic to walk travel time in motion. In some developed countries’ cities, such as in Minneapolis, USA, elasticity of walk travel time for walk varies from 0.14% to 0.26% *(31)*. Minneapolis has a high quality transport system. Its lower elasticity value of walk travel time reflects people's positive attitude toward walking. Contrarily commuters in Dhaka are substantially sensitive to increase in walk travel time.

Elasticity values of travel time in motion for all modes are listed as follows. Bold values represent direct elasticity of the respective mode and trailing values represent cross elasticity of the mode specified within parenthesis.

Bus: **-0.07**, 0.02 (BRT), 0.01 (car & PPT), 0.05 (walk)
BRT: **-0.19**, 0.23 (bus), 0.41 (car & PPT), 0.03 (walk)
Car & PPT: **-3.61**, 0.09 (bus), 0.43 (BRT), 0.05 (walk)

Direct and cross elasticity values of bus travel cost are very close to 0. Therefore, Bus, BRT, CPPT and walk are relatively inelastic with respect to bus travel cost. Of all modes, Walk mode share would increase the most with increasing bus travel cost. Most bus users who cannot afford increased bus fare will not switch to either BRT or CPPT. Very small percentages of commuters would shift to BRT and CPPT in response to increased bus travel cost.

Table 2 lists elasticity values of different modes for different cities. The model result shows that workers are relatively inelastic with travel cost of bus in Dhaka compared with other cities.

Both the direct and cross elasticity of BRT travel cost are less than 1. Therefore, all modes are relatively inelastic to BRT travel cost. Result shows that increased BRT travel cost would have the greatest increase in the probability of CPPT being chosen.

From Table 2 it can be seen that for Chicago the elasticity of travel cost of BRT is 0.17%, which is very similar to that of Dhaka. Both in a developed country's city and in Dhaka commuters are sightly elastic to BRT travel cost. This may be because commuters would reap the benefits of improved BRT service.

As the direct elasticity of CPPT cost is greater than 1, these modes are relatively elastic to travel cost for this mode. Car & PPT is the most expensive travel option for Dhaka. Therefore, commuters would react negatively if car & PPT cost were to increase.

Direct elasticity of CPPT travel cost is considerably high. This is mainly because improved travel options are available in the SC scenario. Direct elasticity of travel cost of car for other cities showed that the values range from 0.23% to 0.32% (Table 2). For Tokyo this value is only 0.06%. Therefore, it can be said that in developed cities people are less sensitive to car travel cost than Dhaka.

CONCLUSION

A mode choice model was developed using Stated Choice data for Dhaka with the inclusion of a proposed Bus Rapid Transit (BRT) system. It showed that workers' mode choice decision is highly influenced by travel cost, travel time in motion, income, age, education level and gender. Male and female commuters who are not poor would widely use BRT for their work trip. However BRT would not be readily taken up by poor commuters because of its high cost. Age and education are also significant influences on workers' mode preference. Analysis showed that mature aged male workers who are not poor and with higher educational qualification have a greater tendency to choose BRT for their work trip. It is postulated that mode choice characteristics for any developing country's city may be similar to Dhaka.

Comparison of elasticity values between Dhaka and developed countries' cities showed similarities and differences between impacts of changes in values of attributes. The presence of good transport system in the hypothetical BRT scenario makes Dhaka workers relatively more elastic with respect to bus travel time in motion. In a developed country's city people are also relatively more elastic with respect to bus travel time in motion. If bus travel time in motion increased, those who can afford would switch to BRT and those who cannot would switch to Walk. However, Dhaka commuters are very inelastic to bus travel cost compared to those of developed cities. This may be because in the BRT scenario bus cost is very low.

Because of less wealth and high cost of other modes Dhaka workers who would use BRT will be relatively less elastic to BRT travel time in motion and travel cost. Contrarily, in developed countries' cities people are relatively elastic to BRT or rapid transit travel time. However, their commuters are relatively less elastic to BRT or rapid transit travel cost.

In Dhaka those who use car & PPT for their work trip would not change to other modes even when car & PPT travel time in motion increases. Contrarily, they would react significantly negatively to increased car & PPT travel cost. However, in the developed country's cities people would react negatively with increased car travel time in motion as they are relatively elastic to car & PPT travel time.

Dhaka workers are highly elastic to walk travel time, whereas in developed country's cities people are relatively less elastic to walk travel time, which is attributed to a more positive attitude towards walk. People in developed countries treat walking as purely a transport mode while those in developed countries appear to also treat walking as a means of physical exercise.

There is limited research on uptake of BRT in Dhaka for the work trip. This research significantly overcomes this gap by establishing probabilities of BRT usage across a range of socio-economic groups. Comparison between developed countries' cities and the Dhaka BRT scenario would be beneficial in informing transport policy for any developing country's city. Future research will ascertain the choice of BRT for other trip purposes. This will also inform transport policy in any developing country's city.

The main limitation of this research is that elasticity from other cities did not combine in vehicle time with bus access time. Another limitation is that because BRT is not yet in operation in Dhaka the model cannot be completely validated. However, utility functions can be applied to forecast future BRT ridership. This model will also be useful to understand the important variables for BRT to be successful in Dhaka and is useful to understand how changes in socio-demographic characteristics change people's preferences towards BRT and other modes.

Another model has been developed for Dhaka with Revealed Preference (RP) data in the another paper. Comparison between the RP and SC models can provide an indication of how transport system conditions may change before and after BRT implementation. Results suggest that about 55% current car users would switch to BRT, about 85% rickshaw users would switch to BRT, about 95% current bus users would continue using BRT, and about 45% current walkers would switch to BRT. About 82% current users who use laguna, taxi, or tempo would switch to BRT.

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TABLE 1 Direct and Cross Elasticity of Travel Time and In-Vehicle Travel Time of Various Modes from Other Studies

City relevant to study or project	Attribute	Direct Elasticity value	Cross Elasticity
Chicago[1]	Rapid Transit Travel Time	Direct elasticity of rapid transit –1.51	
Montreal[1]	Bus and rapid rail in vehicle travel time	Direct elasticity of Bus and rapid rail in vehicle travel time -0.27	
Australia[2]	BRT travel time	Direct elasticity of BRT travel time –0.857	
Australia and New Zealand[3]	Bus in-vehicle travel time	Direct elasticity of bus -0.50	
Karachi city in Pakistan Based on study of Thorbani (1984) [4]	Bus in-vehicle time	Direct elasticity of bus -0.77	Cross elasticity of car 0.03 Cross elasticity of PPT 0.17 Cross elasticity of walk 0.06
Chicago city [5]	Bus in-vehicle time	Direct elasticity for bus -1.10	
San Francisco [5]	Bus in-vehicle time	Direct elasticity for bus ranges from -0.46 to -0.60	
Minnepolis[5]	Bus in-vehicle time	Direct elasticity for bus -0.52	
Chicago[1]	Bus travel time	Direct elasticity of bus travel time –3.03	
East Bay San Francisco[1]	Bus in vehicle travel time	Direct elasticity of bus in vehicle travel time –0.46	Cross elasticity of car in vehicle travel time 0.15
Australia and New Zealand[3]	Car in-vehicle travel Time	Direct elasticity of car in short run -0.3 and in long run -0.6	
Karachi city in Pakistan Based on study of Thorbani (1984) [4]	Car in-vehicle time	Direct elasticity of car –0.04	Cross elasticity of bus from 0.01 to 0.02
Great Britain[4]	Car in-vehicle time	Direct elasticity of car -0.44	
Europe[3]	Car in-vehicle time	Direct elasticity of car -0.62 for short run and -0.41 for long run	
Dutch National Model [1]	Car in-vehicle time	Direct elasticity of car -0.39 for short run and -0.58 for long run	Cross elasticity of bus 0.18 for short run and 0.16 for long run
Italian national model[1]	Car in-vehicle time	Direct elasticity of car -0.54 for short run and -0.56 for long run	Cross elasticity of bus 0.22
Model for Brussels [1]	Car in-vehicle time	Direct elasticity of car -0.23 for short run and -0.26 for long run	Cross elasticity of bus 0.38 for short run and 0.37 for long run
Chicago[1]	Car Travel Time	Direct elasticity of car travel time -0.64	
Minneapolis[5]	Walk travel time	-0.26 for work trip -0.14 for non-work trip	

Source: [1]Hague Consulting Group *(10)*; [2]Hensher and Louviere *(11)*; [3]Wallis and Schmidt *(13)*; [4]BITRE *(3)*; [5]Lago, Mayworm *(14)*

TABLE 2 Direct and Cross Elasticity of Travel Cost of Different Modes from Other Studies

City	Attribute	Direct Elasticity	Cross Elasticity
Chicago[1]	Rapid transit travel cost	Direct elasticity of rapid transit –0.17	
Australia [2]	BRT fare	Direct elasticity of BRT –0.573	
Study on Leeds City[3]	Public Transport travel cost	Direct elasticity of public transport is -0.65	Cross elasticity of car 0.14 Cross elasticity of walk is 0.56
Study on Dortmund City [3]	Public Transport travel cost	Direct elasticity of public transport -0.58	Cross elasticity of car 0.12 Cross elasticity of walk is 0.23
Study on Tokyo City[3]	Public Transport travel cost	Direct elasticity of public transport -0.03	Cross elasticity of car 0.09 Cross elasticity of walk 0.09
Study on UK and Europe [4]	Bus fare cost	Direct elasticity of bus for short run -0.28 and for long run -0.55	
Study on Australia [1]	Bus fare cost	Direct elasticity of bus fare is -0.29	
Chicago [1]	Bus travel cost	Direct elasticity of bus -0.16	
Study on Australia [5]	Bus fare cost	Direct elasticity of bus from -0.18 to -0.22	Cross elasticity of car is 0.1
UK City [6]	Bus Cost	Direct elasticity of bus in the short run from -0.2 to -0.3 Direct elasticity of bus in the long run from -0.4 to -0.6	
UK City [7]	Bus Cost	Direct elasticity of bus in the short run -0.4 Direct elasticity of bus in the long run -1.0	
Sydney [8]	Public Transport Fare	Direct elasticity of public transport –0.15	Cross elasticity of car 0.173
Sydney[9]	Public Transport cost	Direct elasticity of public transport in the short run -0.22 long run -0.29	
Study on Leeds City[3]	car travel cost	Direct elasticity of car -0.29	Cross elasticity of walk 0.06 Cross elasticity of Public transport 0.31
Study on Dortmund City[3]	car travel cost	Direct elasticity of car for its travel cost -0.23	Cross elasticity of walk 0.41 Cross elasticity of Public transport 0.4
Study on Tokyo City[3]	car travel cost	Direct elasticity of car -0.06	Cross elasticity of Public transport 0.03 Cross elasticity of walk 0.03
Chicago [1]	Car travel cost	Direct elasticity of car –0.28	
Sydney[8]	Car cost	Direct elasticity of car –0.094	Cross elasticity of bus 0.08

Source: [3]Luk and Hepburn *(15)*; [5]Hague Consulting Group *(11)*; [1]Banister, Cullen *(16)*; [2]Goodwin *(4)*; [4]Booz Allen & Hamilton *(17)*; [6]Dargay and Hanly *(18)*; [7]Balcombe, Mackett *(6)* ; [8]Taplin, Hensher *(19)*; [9]Tsai, Mulley *(12)*

TABLE 3 Modes, Attributes and Their Levels in the SC Survey

Mode	Travel Time (min)	Travel Cost (US$)
Walk-BRT-Walk	49.5; 44; 38.5; 33	0.06; 0.13; 0.16; 0.20
Walk-BRT-Rickshaw	45; 40; 35; 30	0.32; 0.40; 0.42; 0.45
Rickshaw-BRT-Rickshaw	40.5; 36; 31.5; 27	0.58; 0.64; 0.68; 0.71
Rickshaw	35	1.03
CNG	17	2.06
Car	14	3.87
Walk	45	0

TABLE 4 Different Levels of BRT for the SC Survey

Choice	Travel time (minute)	Bus Comfort
BRT Level 1 (This level is similar to current condition as bus service do not improve)	10% reduction of travel time of Bus from the current travel time (Current average bus speed [1]10 mph, current average bus cost [2]0.02 $US/km)	• Buses have no fans • Buses have no proper seating arrangement • buses have level boarding • narrow bus doors • basic bus stands with shelters • crowded conditions but no service denials • buses arrive predictably at 25 min frequency
BRT Level 2	20% Reduction of Travel Time bus from the current travel time (Current average bus speed [1]10 mph, current average bus cost [2]0.02 $US /km)	• Buses do not have fan • proper seating and standing arrangement • passengers do not have to climb the stairs to get into buses • doors are wide • very basic bus stand with shelter • crowded but condition improved from current condition so passengers can get into buses • buses are not unpredictable and comes every after 20 minutes
BRT Level 3	30% Reduction of Travel Time from the current travel time (Current average bus speed [1]10 mph, current average bus cost [2]0.02 $US /km)	• Buses have fans • proper seating and standing arrangement • no need to climb stairs to board bus • wide doors • moderately crowded • bus stands upgraded with security camera and emergency phone • passengers can board buses easily • most passengers can sit • predictable bus frequency of 15 minutes
BRT Level 4	40% Reduction of Travel Time from the current travel time (Current average bus speed [1]10 mph, current average bus cost [2] 0.02 $US /km)	• All buses have air conditioning (AC) • proper seating and standing arrangement • buses are low lying, do not have to climb the stairs to get into buses • wide doors • very good quality bus; not crowded • bus stands are upgraded with security camera, emergency phone passenger information system • passengers can get into buses easily • most of the passengers can seat • buses are not unpredictable and comes every after 7 minutes

[1] personal observation and assumptions from the survey responses and literature review.
[2]Bangladesh Road Transport Authority *(36)*

TABLE 5 Attributes Used in the Model with SC data

Type of Attributes	Attributes	Description	Variable State	Coded Value
Mode Specific Attributes	Total Cost	Total money (in *BDT) workers spent for work trip		
	Time in motion by any vehicle or time by walking	Total time (in minute) workers are actually moving including any access time to/from public transport.		
Social Demographic Attributes	Income	Those who have income less than or equal to 5000 BDT are considered as **Poor** and those who has income more than 5000 BDT are considered as Not Poor	<=5000 *BDT	1
			>5000 *BDT	0
	Gender	Workers' Gender identity	Male	1
			Female	0
	Education	The sample is divided into those who have a postgraduate degree and those who do not have a postgraduate degree	With postgraduate education	1
			Without postgraduate education	0
	Age	The sample is divided into age less than or equal to 35 years and age above 35 years	<=35 YEAR	0
			>35 YEAR	1
Constant	Walk, car and CPPT Specific Constant			

*BDT= Bangladeshi Currency

TABLE 6 Model Estimation Result for Model Calibrated with Stated Choice Data

Type of Attributes	Attributes	Coefficient	Std. Err.	t-ratio	P-value
Generic Variable	Travel Time in Motion	-0.0661	0.0215	3.0701	<0.01
	Travel Cost	-0.0240	0.0048	4.9720	<0.01
Bus	Postgraduate	-2.3083	0.4495	5.1351	<0.01
	Gender	-0.6368	0.3679	1.7306	<0.01
BRT	Constant	0.8241	0.3822	2.1563	<0.01
	Income 0_5000	-3.4973	0.7584	-4.6115	<0.01
	Age Above 35	0.7129	0.3784	1.8842	<0.01
Car & PPT	Constant	0.7647	1.7094	0.4474	<0.01
	Postgraduate	3.2335	1.0516	3.0749	<0.01
	Age Above 35	2.0941	0.6264	3.3432	<0.01
Walk	Constant	-2.3830	1.0176	2.3418	<0.01
	Gender	-1.7716	0.5935	-.9853	<0.01
	Income 0_5000	3.9353	0.8039	4.8951	<0.01
	Age Above 35	1.4890	0.5245	2.8392	<0.01
Overall goodness of fit of the Model: Log Likelihood Function=-267.000 Pseudo R^2=0.43					